ISSN: 0974-5343
IJMST (2009), 2(3):37-55

A Research Review on Analysis and Interpretation of Arrhythmias using ECG Signals

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ABSTRACT

Arrhythmias or abnormalities of the heart rhythm can be detected using electrocardiograms (ECGs) that record the electrical activity of the heart. However, timely and accurate detection of arrhythmias is a complex decision-making process for a cardiologist due to contamination of ECG signals with different frequencies of noise and coexistence of two or more arrhythmic events in one abnormal cardiac rhythm. For reliable interpretation of real-time ECGs, a plethora of computer based techniques based on digital signal processing of ECG waveform have been reported. Through the use of different rhythm analysis techniques viz., time domain and frequency domain techniques, it is possible to extract vital diagnostic features present in an ECG record. Recently, artificial intelligent tools such as neural networks, genetic algorithms, fuzzy systems, and expert systems have frequently been reported for detection and diagnostic tasks. Expert systems that are IF-THEN rule based systems (knowledge-based systems) form a major part of clinical decision support systems in practice. Non-knowledge based expert systems that are not rule based, form a major component of hybrid artificial intelligent systems such as fuzzy-neural networks or expert systems using genetic algorithms. This paper, therefore, reviews the progress made in the field of cardiac rhythm analysis and interpretation since its inception. Attempts are made to highlight the current and future issues involved for the development of automated arrhythmia analysis and interpretation. A list of 207 research publication on the subject is also appended for a quick reference.

Keywords: Arrhythmia; ECG analysis; ECG interpretation; Noise removal; Expert system; Artificial intelligence; Feature extraction

INTRODUCTION

Cardiac arrhythmias occur when disturbances are caused in the normal electrical events related to the basic process of automaticity, conduction and triggering mechanisms of the heart. Heart diseases, specially coronary artery disease, defective heart valves, or a weakened heart, more commonly cause arrhythmias. Arrhythmia interpretation is a very important task performed in Coronary Care Units (CCUs) and ambulatory electrocardiogram (ECG) monitoring systems. If not well diagnosed in time, they represent a serious threat to the patient.

Therefore, there is a need for quick identification of these abnormal electrical activities of the heart. Both life threatening (e.g. ventricular fibrillation and atrial fibrillation) and not-so-life threatening arrhythmias (e.g. premature ventricular contraction and atrial premature contraction) can be detected by using the ECG that records the electrical activity of the heart [1].

A standard ECG record is the best test for diagnosing all arrhythmias, whether of ventricular or supraventricular origin. An ECG tracing is a series of waves that represent the electrical events of the various chambers and conduction pathways within the heart. The electrical activity during the cardiac cycle is characterized by five separate waves of deflections designated as P, Q, R, S and T. The configuration of one complete ECG cycle or beat demonstrating the wave intervals and segments normally observed in the ECG is shown in Fig. 1.

A normal ECG rhythm is the ordered sequence of depolarisation of the myocardial cells [2], i.e. the sequence of P wave (atrial myocardial depolarisation) and QRS wave (ventricular myocardial depolarisation) generation, at a regular rate of 60-100 beats per minute (bpm). When this sequence is disturbed, abnormal rhythms or arrhythmias occur. An arrhythmia is characterized on an ECG as a deviation from the normal sinus rhythm in rate, regularity or as a different pattern of activation of the cardiac muscle. Rhythm analysis to diagnose arrhythmias involves the accurate detection of P waves and QRS complexes with respect to time, with respect to each other and with respect to space. Arrhythmia monitoring is performed generally using ECG lead II, since both the P waves and QRS complexes are observed clearly in this lead [1-4].

Computerized ECG interpretation to detect arrhythmias (off-line or on-line) is a process of ECG data acquisition, waveform recognition, measurement of wave parameters and rhythm classification. A plethora of computer based techniques have been

reported to detect the abnormalities of the heart rhythm. Different methods for arrhythmia detection based on digital signal processing of ECG waveform are available in literature. This paper, therefore, deals with a state-of-the-art discussion on analysis and interpretation of arrhythmia, highlighting the analytical and technical considerations as well as various issues addressed in the literature towards practical realization of this technology to assist cardiologists and other health professionals for reliable interpretation of arrhythmias from real-time ECG signals. Two hundred seven publications [1-207] are reviewed and classified in seven parts.

BRIEF HISTORY OF ARRHYTHMIA ANALYSIS

The ECG tracings depicting arrhythmias were shown, for the first time by Einthoven, in the beginning of the last century, sometime around 1905-06 [31] [5]. Concept of ECG rhythm monitoring was also described in the paper. However, identification of abnormal rhythm and associated parameters, in a recorded ECG, proved to be a complex task for cardiologists.

As the invention of transistor led to the development of commercial computers, researchers working at MIT and Lincoln labs in 1961 used the technology of the time to build a transistorized minicomputer called LINC that served as a very useful computational facility for biomedical applications [6]. ECGs could be acquired from patients directly and displayed on its graphics display. Such developments had a great impact on research workers trying to monitor ECGs and evolve methods of automated rhythm analysis.

Also, the discovery of Holter monitoring system in 1961, helped to record long-term ECGs that provided the cardiologists the ECGs, with episodes of randomly occurring rhythm abnormalities and sudden beat change. Around this time period of late 1950s and early 1960s, several attempts were made to perform computerized ECG interpretation to identify arrhythmias and other cardiac disorders.

The pioneering work to accomplish analysis of ECG, by a digital computer, was initiated in 1957 by Pipberger and his co-research workers [7]. Pipberger's group described digital conversion of ECGs for the first time at the American Heart Association's 1959 Scientific Sessions and in Circulation in 1960 [8]. Results from a pilot project designed to demonstrate the feasibility of screening of normal and abnormal ECGs were reported by them in 1961 [9]. Stallman and Pipberger in 1961 described a more comprehensive automatic ECG wave detection and measurement program [10].

More and more publications ushering in, during this period, created a revolution in the design and development of computer based ECG analysis systems [11-17]. Impeccable drive to develop computer based ECG analysis systems, led to the conceptualization of two basic approaches, for computerized interpretation of the ECG by early 1970s:

(i) Decision logic approach based on the IF-THEN rule formalism that is easily followed by a human expert. It is basically a rule based expert system.

(ii) Multivariate statistical pattern recognition method in which ECG interpretation as a pattern classification task is employed where decisions are made on the basis of the theory of probabilitybase

Early attempts to perform arrhythmia classification, in digital computer ECG diagnostic systems, were carried out in varying degrees [18-32], and several algorithms for identification of cardiac arrhythmias were proposed In 1977, Bemmel presented [33] a review of the state of the art of computer applications in cardiac and pulmonary function laboratories. He reported that in CCUs and ambulatory ECG monitoring systems, detection of R waves was generally accomplished to identify R-R intervals, ectopic beats and ventricular fibrillation.

Researchers working at the University of Wisconsin-Madison, in 1978, published their contributions to ambulatory ECG monitoring for detecting rhythm abnormalities [34-38]. Murthy et al. in 1979 [39] proposed a new scheme for the detection of VPBs, wherein the first difference of the digitized ECG was transformed into a single positive peak with no ripples for each ECG cycle, for detection and delineation of QRS complexes. Linear discriminant function parameters were used to classify the complexes. In 1980, Udupa and Murthy [40] presented a diagnostic system for ECG rhythm monitoring based on syntactic approaches to pattern recognition. The scheme relied on the morphological differences between normal and arrhythmic ECG patterns. The normal and abnormal ECGs were recognized using a set of seven slope symbols as primitives. VPB, bigeminy, bradycardia, tachycardia, sinus arrhythmia and normal ECG were classified using lead II signals.

Fancott and Wong in 1980 [41], presented a minicomputer system software for the analysis of 24 hr ambulatory ECG tape recordings at 60 times real-time. Murray et al. described their effort, in 1980 [42], to develop programs for a microprocessor based unit to provide contour analysis and interpretation of 3 lead

ECG signals. The analysis system incorporated the diagnostic criteria of the American Heart Association. Decision tables were framed on the basis of diagnostic rules designed to match the patients' data. The decision tables provided an effective logical approach to classify ventricular conduction defects, pre-excitation, ventricular enlargement and A-V conduction disorders.

Tompkins in 1980 [43] presented the modular designs of portable, battery operated arrhythmia monitor for ambulatory patients and a portable battery powered arrhythmia monitor /recorder for the operating room that enabled the physician to view arrhythmic events shortly after they occurred, rather than waiting for several days, as in the Holter approach for the data to be scanned and returned. QRS complex detection based arrhythmia interpretation technique, was employed to classify bradycardia, tachycardia, asystole, ventricular fibrillation, skipped beats, PVCs, R-on-T PVC, bigeminy, trigeminy, APB and A-V blocks.

The advent of the PC motivated the biomedical engineers, physicians and research workers to gather momentum for pursuing the design and development of reliable and real-time ECG rhythm analysis and interpretation systems. Some of the major contributions 1980s onwards, in the field of cardiac rhythm analysis and interpretation, are briefly described below under the broad categories of (i) Signal pre-processing or noise removal from ECG recordings, (ii) Rhythm analysis or feature extraction from recorded ECG, and (iii) Arrhythmia detection based on rhythm analysis.

ELIMINATION OF NOISE FROM ECG SIGNALS

ECG noise is ubiquitous; it is present in operating rooms, in physiological laboratories, and in patient wards. Noise from power line interference (50 or 60 Hz), EMG from muscles, motion artifact from the electrode and skin contact interface, and multi-frequency noise due to electronic equipment in the surroundings of the patient are the various types of interference that contaminate an ECG signal. Elimination of this ECG noise is, therefore, the first step in ECG analysis and interpretation. However, removal of multiple frequencies is not a simple process. Suppression of noise usually causes ECG signal distortion leading to inaccurate interpretation. In spite of this stringent condition that imposes a trade-off between obtaining a noise free ECG, and accuracy of ECG analysis and classification, researchers have developed a number of techniques to extract useful diagnostic features from ECG signals contaminated by different types of interference. Some of these methods require pre-processing for noise elimination prior to feature extraction, while some detect the ECG characteristic in presence of noise. Some of the key works are given in [44-53].

In 1995, Ider et al. [54] proposed a technique for removal of power line interference from signal averaged ECGs. The method was referred to as the Line Interference Subtraction filter (LIS) and was based on the subtraction of a scaled and shifted version of a common mode line interference signal, simultaneously recorded, from the ECG.

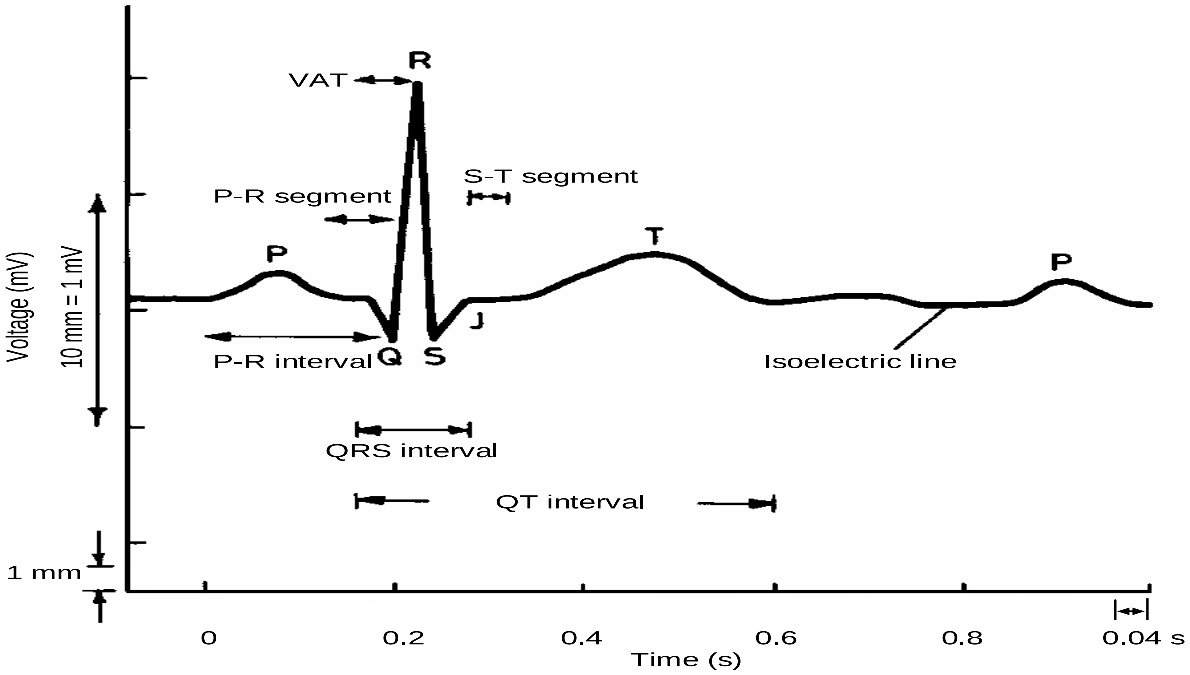

Fig. 1. Normal ECG cardiac cycle

In 1991, the Task Force Committee of the European Society of Cardiology, the American Heart Association, and the American College of Cardiology issued a statement discouraging the application of notch filters for removal of 50- or 60-Hz power line interference from ECG signals, especially the signal averaged ECGs [55]. The reason was that, optimization of the stop band of notch filters (FIR or IIR digital filters) resulted in an undesired transient response that distorted the filter output on the start-up. To suppress the transient response of IIR notch filter, used for eliminating AC interference in ECG, Pei and Tseng, in 1995 [56], presented a technique based on the vector projection of the first few samples of the input signal (responsible for transient behaviour). The method performed better than the conventional notch filter with arbitrary initial condition, by providing better initial values for the IIR notch filter output.

In 1997, Sahambi et al. [57], used wavelet transform to obtain multiscale analysis for timing characterization of the ECG. The technique helped to detect the QRS complex, P and T complexes with positive and negative polarity, PR, QT and ST segments in the presence of noise, without preprocessing the signal. Baseline drift, power line interference, and a combination of both were the interference considered.

The wavelet employed was the first derivative of a smoothing function (Gaussian function), that reduced errors, in ECG timing interval characterization, in the presence of noise. The technique was tested using records 106 and 202 of the MIT/BIH database. Ma et al., in 1999 [58], presented a fast recursive least squares (FRLS) adaptive notch filter (ANF) for removal of sinusoidal interference from recorded biomedical signals, including ECGs contaminated by 50/60 Hz power line interference. Rakotomamonjy et al. in 1999 [59] described a new wavelet-based filtering method to improve the signal-to-noise ratio of the signal averaged ECGs.

In order to accomplish baseline correction and noise suppression with minimum signal distortion, Sun et al. [60] in 2002 presented a modified morphological filtering (MMF) technique. It was shown that MMF performs well in terms of filtering characteristics, low signal distortion ratio, low computational burden as well as good noise suppression ratio and baseline correction ratio.

Suppression of an impulsive noise in ECG signal was addressed by Pancer in 2004 [61]. Kim et al. [62] in 2006 grouped various noisy signals into six categories by context estimation and effectively reconfigured noise reduction filter by applying neural network and genetic algorithm. Chavan et al. in 2008 [63] designed and developed a digital FIR equiripple filter to reduce power line interference. Due to higher order design of filter, increase in the computational complexity was observed. A few of the prominent techniques for noise cancellation are summarized as [64]:

i. Smoothing filters or moving average filters to cancel high frequency noise, viz., 60 Hz AC interference, motion artifacts and quantization error: Hanning filter and least-square polynomial smoothing filters.

ii. Notch filters, bandstop, or band-reject filters, that have a zero placed on the unit circle at the site corresponding to the frequency of cancellation.

iii. Filters based on the derivative algorithm: Two-point difference, three-point central difference, and least-squares polynomial derivative approximation filters.

iv. IIR (infinite impulse response) filters: Integrators based on rectangular, trapezoidal and Simpson's rule, and, second-order recursive filters.

v. Integer filters: Lynn's integer filter design.

vi. Adaptive filters used for cancelling 60 Hz AC interference, enhancement of P waves and removal of other types of noise from ECG signal.

vii. Signal averaging, generally preferred when useful ECG signal components and noise overlap. The method reduces noise without distorting the signal.

viii. Frequency domain filters based on FFT (Fast Fourier Transform), DFT (Discrete Fourier Transform), computation of correlation and convolution in the frequency domain, and estimation of the power spectrum.

ix. Wavelet transform methods

DETERMINATION OF ISOELECTRIC LINE IN ECG

The isoelectrical period in electrocardiology is the reference against which the instantaneous magnitudes of ECG signal components are determined. This period is not a clearly defined portion of the ECG, especially when the heart rate is high enough, making this period too short to be used or nor present at all. Ideally, the reference level against which the magnitude of the recorded ECG is to be measured should represent zero activity of the signal source.

Unfortunately, in most cases the zero level of ECG signal deviates from zero voltage, and it is generally difficult to determine its exact value [65]. However, the idea of the isoelectric period of the recorded ECG being taken as the reference level is not sufficient, and, that the isoelectrical period in the ECG denotes the true level of zero heart action does not produce desired results. Difficulty in determining the exact instant when ventricular activity ends, the end of the T wave extending into the assumed isoelectrical period, high heart rate, distortion of the signal by EMG, respiratory activity creating baseline wander, render discrimination between the tail of the T wave and the onset of isoelectrical period quite problematic, and deformation of the ECG signal during the assumed isoelectrical period by ischemic currents flowing through the heart [66-68], create numerous difficulties in determining the exact baseline in an ECG to accomplish feature extraction.

As per CSE Working Party's updated AHA recommendations [69], the ST- segment, the T wave and the P wave, should all be measured w.r.t. the isoelectric part of the tracing before the P wave. CSE Working Party recommended that a uniform horizontal baseline should be determined in an interval before QRS onset for all QRS and ST-T measurements in such a way so that problems arising due to the earlier AHA recommendations, in which a discontinuity is implied in the baseline immediately after the J point, could be avoided.

Inspite of these recommendations, ambiguity still remains especially in cases of arrhythmic signals, and the problem deepens when the arrhythmic ECGs are corrupted by multiple frequency noise. Peper et al. [70], in 1990, developed a method to compute a reference value, independent of isoelectric period and heart rate. The method was derived from a technique developed for the separation of the surface His-Purkinje signal from the P wave in case of overlap. In the derived technique, two successive heart beats were separated on the basis of the original technique, highlighting the signal level at zero heart activity. This signal level was used as zero reference in ECG signals, and provided accurate results.

Identification of a noise-free baseline may be a difficult process, but investigators have tried their best to combat this problem. Whether it may be visual interpretation of an ECG by a cardiologist, or a computer based ECG analysis system, baseline wander, due to respiration and electrode impedance changes caused by perspiration, always creates extraneous low frequency components which severely influence ECG interpretation. The frequency content of the baseline wander is generally below 0.5Hz. However, baseline wander activity increases with increased body movements.

A number of methods have been reported in literature to obtain noise free baseline or to remove baseline wander [71-76]. Researcher used linear interpolation and cubic splines to construct a baseline by interpolating between the isoelectric levels identified from the P-R intervals [71, 72, 73], employed linear phase to obtain baseline drifts reduction [74] , applied time-varying digital filtering and adaptive noise canceller to obtain a drift-free baseline [75, 76].

Leski and Henzel in 2005 [77] presented a new class of nonlinear filters for reduction in powerline interference and deal with problems of baseline wander. In 2007, Sayadi and Shamsollahi [78] presented a new modified wavelet transform, called the multiadaptive bionic wavelet transform (MABWT), to remove noise from ECG signals under a wide range of variations for noise. The procedure largely proved advantageous over wavelet-based methods for baseline wandering cancellation, including both DC components and baseline drifts.

ARRHYTHMIA ANALYSIS

Various pattern recognition techniques are used to perform rhythm analysis of ECG signals to obtain diagnostic arrhythmia analysis. The major techniques can be categorized as follows [79]:

- non-syntactic methods
- syntactic methods, and
- hybrid methods

The non-syntactic methods employ techniques from classical signal processing viz., template correlation, matched filters, threshold triggers, frequency domain analysis; wavelet transforms etc. as well as heuristic techniques. The syntactic methods utilize techniques from the syntactic pattern recognition field. The hybrid methods are an amalgamation of the non-syntactic, syntactic, and artificial intelligence methods such as neural networks, genetic algorithms, fuzzy logic etc. Major research contributions in these areas from 1980 to 2000 are presented in [80-107]

In 2001, Hamde [108] presented the use of multiresolution signal decomposition to evaluate the performance of the detection of QRS complexes with five different types of existing wavelets. A new wavelet, the 6th one, was constructed based on the evaluation study, to perform reliable QRS complex detection.

Carlson et al. [109, developed a method to discriminate between abnormal P wave morphology, due to atrial conduction defects, and normal P waves. The technique was based on impulse response analysis of the P wave, and linear discrimination, for normal and abnormal P wave parameter classification. Three independent classification methods were studied: the Fisher linear discriminant, the spectrum of discrete Fourier transform (DFT), and the duration of the P wave.

Bartolo et al. in 2001 [110], presented a QRS detection software based on QRS template matching process to detect abnormalities in the cardiac rhythm that generally occur in patients with sleep disorders. Prior to QRS detection, ECG signals were preprocessed, to remove 60 Hz interference by using a 3-point FIR notch filter, and, to reduce baseline wander by using a running median filter. The technique failed to identify any change in QRS morphology or timing w.r.t. the prevalent QRS waveform, and as a result most of the undetected PVCs were classified as normal beats.

Again in 2001, Botter et al. [111], proposed a backward-error-propagation neural network with asymmetric basis functions, for extracting P wave features in surface ECGs. The network extracted 9 parameters for describing P waves; the parameters could later be used for pattern clustering or classification tasks. Almeida et al. [112] in 2003 reported a wavelet-based multiscale approach for automatic detection and delineation of P and T waves for a wide range of morphologies. The algorithm detected annotated P and T waves with high sensitivity and delineated them with errors comparable with the accepted differences between cardiologists.

Ravier and Buttelli in 2004 [113] introduced a new QRS waveform detector for detecting QRS complex in difficult recording conditions with highly non-stationary noise as well as time-varying QRS complex morphology. For this purpose, a smoothed matched filtering was realized on specific wavelet coefficient patterns in the time-scale plane. The detection was enhanced using the family of Klauder wavelets which demonstrate similarities to ECG waveforms.

Some of the recent works for detection of QRS complex, P- and T-wave are reported in [114-121]. Darrington in 2006 proposed a method for the detection of QRS complexes [115]. This method applies the algorithm proposed in [122] to a shifting window over the ECG signals. The method was tested on the MIT/BIH arrhythmia data base. A simple moving average-based computing method for real-time QRS detection along with a wavelet-based de-noising procedure to effectively reduce the noise level was reported by Szi-Wen Chen et al. [116] in 2006.

An intelligent ECG diagnostic tool, based on a two-stage feed-forward neural network, that can recognize heart abnormalities while reducing the complexities, cost and response time of the system was discussed by Hosseini et al. in 2006 [117]. Meyer et al. in 2006 developed a frame work for combining state-of-the-art algorithm for detection of QRS complexes in ECG signals; namely PT (Pan-Tompkins) and wavelet algorithms [118]. In this, both algorithms are run in parallel. When both the methods disagree to predict a QRS complex in a particular time window, a data driven strategy for deciding whether or not to accept the candidate QRS complex is applied. In case of disagreement, authors have suggested to locally return to PT method with a modified threshold, accepting the result of the local return as the final decision. Arzeno et al. [119] in 2008 analyzed the traditional first derivative based squaring function (Hamilton-Tompkins) and Hilbert transform based method for QRS detection, and have suggested some modifications with improved detection threshold.

Ghaffari et al. [120] presented in 2008 a new mathematical based QRS detector using continuous wavelet transform. In order to magnify QRS complex and to reduce the effects of other peaks, the concept of dominant re-scaled wavelet coefficient is defined. Using this concept, the relation between the time duration of components of a QRS complex and wavelet transform are derived.

Puero et al. [121] in 2008 proposed two new indices to quantify ischemic changes during depolarization describing the upward and downward slopes of QRS complex. The more commonly used QRS high-frequency index ($I_{\mathrm{HF}\ (150,\ 250)}$) was been found to decrease in patients with ischemic heart disease when compared to healthy individuals.

Recently, Mitra et al. in 2009 [123] presented a technique for online analysis of tilted ECGs due to respiration and presence of power line oscillations to detect different ECG wave parameters using pattern defined heuristic rules and directional histogram. Mehta and Lingayat in 2009 [124] presented a method for the detection of QRS complexes in 12-lead ECG using support vector machine (SVM). Digital filtering techniques were used to remove base line wander and power line interference. The proposed method functioned reliably even under conditions of poor signal quality in ECG data.

The Bayesian filtering paradigm was used by Sayadi and Shamsollahi in 2009 [125] for ECG beat segmentation and extraction of fiducial points.

Analytic expressions for the determination of points and intervals were derived and evaluated on various real ECG signals. Simulation results showed that the method can contribute to and enhance the clinical ECG beat segmentation performance.

ARRHYTHMIA INTERPRETATION

Detection of arrhythmias is a complex decision-making process for a cardiologist. Advent of artificial intelligent (AI) techniques, like expert systems, have provided sophisticated tools to suitably support medical decisions made by a cardiologist. Over the years, researchers have also employed non-AI techniques such as Fourier transforms, wavelet transforms, Kalman filtering etc. for interpreting ECG records.

Arrhythmia Interpretation using Conventional Techniques

In 1987, Chen et al. [126], Guillen et al. [127], and, Hamilton and Tompkins [128], presented their work, to detect ventricular fibrillation by employing regression test of autocorrelation function [126], to differentiate between ventricular fibrillation and ventricular tachycardia by computing the time-series analysis and modeling [127], and, to detect ventricular fibrillation and ventricular tachycardia by adaptive modeling [128], respectively.

Zhu and Thakor in 1988 [129], presented a technique that used adaptive recurrent filter for learning the morphology of ECG signal complexes, viz., the P-QRS-T sequence that recurs with each heart beat, and for detecting transient variations. Chang et al. in 1988 [130], employed Fourier descriptors (FDs) of an ECG and a synthetic VCG (SVCG) to discriminate between normal beats and PVCs. Ropella et al., in 1989 [131], discriminated between fibrillatory and nonfibrillatory cardiac rhythms by computing the coherence spectrum.

Barro et al. in 1990 [132], on the basis of heart rate, end of previous beat's T-wave, R-R interval, QRS width, average R-R interval and QRS morphology, attempted to classify normal, supraventricular and ventricular beats. Rhythm abnormalities, viz., bigeminy, trigeminy, bradycardia, atrial fibrillation and ventricular flutter-fibrillation (classified on the basis of frequency domain analysis of ECGs) were also detected.

Malik et al. in 1990 [133], presented a method based on Smirnov test and chi-squared test to analyze Holter recordings. The ECGs were subjected to multiple random sampling before these statistical approaches were used to quantify the density of VPBs and to compare the density of VPBs in different recordings. In 1991, Woolfson [134] applied Kalman filtering to compute time varying spectra of the R-R intervals to detect bigeminy, trigeminy, second degree heart block and ventricular flutter in ECG records acquired from the MIT/BIH database.

Again, in 1993, Voudouris et al. [135] developed an improved hidden Markov Model (HMM) structure, to characterize cardiac arrhythmias in multiple-lead ECG recordings, and also proposed a procedure to apply HMM for analyzing single lead ECGs. HMM is a statistical method that can be used to categorize an observed data sequence by a multidimensional probability density function. It was concluded that the multi-lead HMM method performed better than the single-lead HMM method to classify cardiac arrhythmias. In 1993, Clayton et al. [136] presented a comparison of 4 techniques, two based on time domain analysis and two based on frequency domain analysis, for detection of ventricular fibrillation from the recorded surface ECGs, of CCU patients, sampled at 250 Hz. The 4 techniques compared were: threshold crossing intervals, peaks in the autocorrelation function, signal content outside the mean frequency, and signal spectrum shape. Pinciroli et al. in 1993 [137] presented an approach for monitoring paroxysmal atrial fibrillation (PAF) on the basis of the morphology of R-R interval series and derived series histograms.

Clayton and Murray in 1993 [138] categorized ventricular fibrillation on the basis of two different approaches - FFT spectral estimation and maximum entropy spectral analysis. Zhou et al. in 1993 [139] used cluster analysis (canonical discriminant analysis) to classify ventricular conduction defects viz., complete LBBB, complete RBBB, undetermined type complete block, left anterior fascicular block, left posterior fascicular block, incomplete LBBB, and incomplete RBBB, on the basis of QRS duration, T axis angle (frontal), T amplitude in V1, QRS axis angle (frontal) and QRS/T spatial angle. The study presented promising results specially for classifying complete LBBB and complete RBBB.

In 1995, Afonso and Tompkins [140] presented detection of ventricular fibrillation by employing time-frequency analysis techniques. Short term Fourier transform (STFT), Wigner distribution (WD), smoothed pseudo Wigner-Ville Distribution (SPWVD) and cone-shaped kernel distribution (CKD) were the time-frequency distributions used to develop arrhythmia classification algorithms.

In 1995, Arthur et al. [141] presented a technique that computed the phase spectra of signal averaged ECGs

(SAECGs), acquired as the Frank X-, Y-, and Z-lead signal averaged ECGs, to identify ventricular tachycardia in patients convalescing from myocardial infarction. Phase spectra from SAECGS were computed, for the complete cardiac cycle, w.r.t. three fiducial points, viz., onset of the P-wave, onset of the Q-wave, the negative slope of the phase for frequencies in the band.

In 1996 Chen et al. [142] presented an algorithm for cardiac arrhythmia classification which was an improvement over the algorithm described by Thakor et al. [143] in 1990. Thakor et al. described a technique for differentiating ventricular fibrillation from ventricular tachycardia using a sequential probability ratio test (SPRT). Chen et al. [142] developed a modified SPRT algorithm that employed a feature referred to as blanking variability (BV) for discriminating between the two life threatening ventricular arrhythmias more accurately. Another technique was presented in 1997 by Khadra et al. [144], for detection of ventricular fibrillation (VF), ventricular tachycardia (VT), and atrial fibrillation (AF), based on the wavelet transformation. The raised cosine wavelet transform (RCWT) was the time-frequency wavelet method being used to obtain information regarding the frequency contents of the P-, QRS-, and T-waves against time. VT was defined by two distinct frequency bands 2-5 Hz and 6-8 Hz. AF was characterized by the frequency band 0-5 Hz, and VF was determined by continuous bands in the range of 2-10 Hz.

Chen [145] in 2000, differentiated amongst VF, VT and supraventricular tachycardia (SVT) using a total least squares (TLS)-based Prony modeling algorithm that derived two features, energy fractional factor (EFF) and predominant frequency (PF), from the ECGs of the MIT/BIH database to classify VF, VT and SVT rhythms. Lepage et al. [146] in 2001 presented a P-wave segmentation method for automatic classification of people prone to atrial fibrillation (AF), one of the most frequent heart arrhythmia. The segmentation procedure, based on hidden Markov models and wavelets, took into account some statistical properties of the signal as well as some electrophysiological properties.

In 2001, Stridh and Sörnmo [147] presented a method for analyzing AF, in the recorded ECGs, by QRST cancellation based on a spatiotemporal signal model that accounted for dynamic changes in the QRS morphology. QRST cancellation was also performed by the average beat subtraction (ABS) method that is sensitive to variations in QRS morphology primarily due to respiratory activity. A comparison of both the techniques showed that the spatiotemporal method for QRST cancellation performed better than the ABS method.

In another study, Stridh et al. in 2001 [148], characterized AF in the surface ECG by time-frequency analysis that enabled to reliably detect subtle short-term and long-term changes in the frequency of fibrillatory waves. Wigner-Ville distribution was used to perform short-term analysis, and Choi-Williams distribution was considered for performing long-term analysis of AF rhythm. Before applying these time-frequency analysis techniques, to describe the AF signals, the ventricular activity was separated from the atrial activity, in the ECG signals under study. In 2003,

Roberts et al. [149] performed rhythm classification using reconstructed phase space (RPS) of signal frequency sub-bands to differentiate atrial arrhythmias from sinus rhythm and ventricular arrhythmias. When the sub-band RPS probabilities were combined in a Bayesian maximum likelihood classifier, the overall classification accuracy increased.

De Chazal et al. in 2004 [150] developed a method for ECG processing for classification of heartbeat into five groups – normal beats, VEBs (ventricular ectopic beats), SVEBs (supraventricular ectopic beats), fusion of normal and VEBs, and unknown beat types. The heartbeat fiducial points were determined manually. Classification performance of 12 classifier configurations were compared and the best configuration chosen for an independent performance assessment. The configuration implemented two linear discriminant classifiers which combined the classifier outputs to form the final decision. In 2005, a technique based on wavelet aided SVM (support vector machine) analysis was presented by Ghosh et al. [151] for cardiac abnormality detection using ECG signals. The method provided good diagnostic accuracy.

Arrhythmia Interpretation using AI Techniques

Within the area of applied Artificial Intelligence (AI), a number of techniques are currently employed in almost every sphere of intelligent computer-based systems. Each technique employs a different emulation of human intelligence and is applied to problems which complement its strengths. The major AI techniques presently in use are: neural networks; genetic algorithms; fuzzy systems; and expert systems [152-157].

An expert system based upon the knowledge-based system approach explicitly embodies expertise and knowledge within the software. Such a knowledge-based system is a program designed to solve problems at a level comparable to that of a human expert in a

given domain [158, 159]. Expert systems may be classified into two broad categories:

i. *Knowledge-based systems:* Expert systems which are IF-THEN rule based. Such systems form a major part of clinical decision support systems (CDSS) in practice.

ii. *Nonknowledge-based systems*: Expert systems that are not rule based. Such systems form a major component of hybrid AI systems. These include, e.g., fuzzy-neural networks, expert systems using genetic algorithms and (or) neural networks and (or) fuzzy systems.

The choice of a hybrid system depends on the problem at hand and the answers needed. In practice, because of the unavoidable existence of uncertainty in clinical data, hybrid AI systems may use fuzzy logic, reasoning rules and probabilities to represent knowledge with uncertainties [160]. Although, more the integration of different AI concepts, more is the complexity involved which at present is generally restricted to research point of view only, rather than being recommended for any commercial or practical clinical application [117, 153, 161-163].

EXPERT SYSTEMS FOR ARRHYTHMIA ANALYSIS

Nonknowledge-based Expert Systems for Arrhythmia Analysis

In 1989, Lee [164], presented a technique using a translation-invariant neural network to diagnose cardiac arrhythmias. A back-propagation neural network was used with a 51-7-3 configuration. Attempts were made to make the input of the network insensitive to rate and shape changes within different ECG signal types. The network was trained and tested using 54 recorded ECGs. Normal sinus rhythm (NSR), ventricular tachycardia (VT) and ventricular fibrillation (VF) were classified. The results for classifying VF beats were found to be inconclusive [165], the ANN wrongly classifying them as normal or VT.

Lin and Chang in 1989 [166], used linear prediction in an associative memory model to classify normal QRS and PVC patterns. Again in 1989 [167], Lin and Chang published another paper communicating that processing ECG signals by Durbin's linear prediction algorithm, provides the residual error signal, which helps to classify PVCs in ECG signals.

Also, in 1989, Pietka [168] classified LBBB and RBBB, SVPBs and VBs, in addition to normal/abnormal beats, using a back-propagation network with 5 nodes in the input layer, two hidden layers with a variable number of nodes and six nodes in the output layer. Five features were used to detect these beats, viz., QRS duration, P-Q interval, R-R rate and the delay in negative slope in V1-V2 and V5-V6. References [169-175] address the work reported from 1990 to 2000.

Wang et al. in 2001 [152] proposed a novel approach for arrhythmia detection based on the concept of short-time multifractality. Cardiac rhythms were characterized by short-term generalized dimensions (STGDs) and then presented to an advanced fuzzy Kohonen network (AFKN) to increase the accuracy of classification. Short-term multifractality reflects both non-linearity and non-stationarity of ECG signals, and is an effective analytical method based on fractal geometry technique. Sixty episodes each of AF, VF and VT were analyzed by the technique developed.

Osowski and Linh in 2001 [176], presented a new approach for recognition and classification of arrhythmic beats with less sensitivity to morphological variation of the QRS complex. Statistical features of the QRS complexes were computed using the 2^{nd}, 3^{rd}, and 4^{th} order cumulants to obtain the 5 point transformed data representing each cumulant. Effectively, each beat (QRS complex) was stored as a statistically transformed QRS complex and the feature vector, thus contained 15 elements. Three more elements were added to the feature vector to characterize every beat by an 18 element vector. The 18 element feature vector was presented to a fuzzy hybrid neural network consisting of two subnetworks connected in cascade. The first network was a fuzzy clustering layer that performed the pre-classification task. The second network was the multilayer perceptron (MLP) that worked as the final beat classifier. Seven types of beats were recognized and classified by this fuzzy hybrid network. The main characteristics of the method were good recognition rate and real-time performance. The technique was an improvement over earlier works based on ANN techniques [177], Fourier-transform neural network [178], and frequency analysis of ECG with maximum entropy method.

In 2004, a method based on wavelet transform and fuzzy neural network (FNN) was used by Shyu et al. [179] for detection of ventricular premature contraction (VPC) from Holter ECG. Using a quadratic spline wavelet to extract features and FN to identify VPS, a 99.7% classification rate was achieved. However, FNN could not distinguish the left bundle branch block (LBBB) symptom from VPC implying that more characteristics of LBBB other than those investigated were required for effective classification.

Ravier et al. in 2007 [180] redefined classical performance evaluation tools in entire QRS complex classification system consisting of a detector followed by a classifier, and evaluated the effects induced by QRS detection errors on the performance of heartbeat classification processing. Performance statistics were given considering MIT/BIH database records that were replayed on a real-time classification system composed of the well-known Hamilton and Tompkins [90, 91] detector followed by a neural network classifier.

Polat and Güneşa in 2007 [181] developed a differential expert system approach with two stages for detection of arrhythmias using principal component analysis (PCA) and least square support vector machine (LS-SVM). In the first stage, dimension of arrhythmias dataset with 279 features was reduced to 15 features using PCA. In the second stage, diagnosis of arrhythmias was conducted by using LS-SVM classifier. The dataset used in the study was from the University of California machine learning database.

Knowledge-based Expert Systems for Arrhythmia Analysis

Expert systems based on hybrid AI techniques provide little insight into how decisions are made or what is the declarative knowledge structure, thereby creating difficulties for human experts to understand such systems [163]. The field of medical diagnostics cannot afford to rely on inaccurate or approximate solutions for obvious reasons. Interpreting a disease, e.g., an abnormal cardiac rhythm leading to fatal heart conditions, requires a software that should be clearly structured and include all possible basic facts, procedural rules and heuristics related to the problem. Also, the decision making process should be easily followed by a cardiologist. The best choice in such cases, as also opted for in modern commercial instrumentation used to interpret ECGs, is the rule-based (or IF-THEN rule based) expert system, that can mimic the human expert's decision process quite closely [123, 163, 182-187].

The success of a rule-based expert system results from its capability to use heuristics besides the domain dependent knowledge available in literature. To whatever extent, a subject of study may be clearly documented and practised as a profession, for instance cardiology, there are no well defined solutions in literature to interpret real time rhythms.

The knowledge a human expert possesses in the field is not laid down in clear definitions or unambiguous algorithms, but is found existing in the rules of thumb (heuristic knowledge) and facts patiently assimilated and learned through years of experience.

Also, sensitivity and stability characterize the performance of a diagnostic expert system. Sensitivity refers to immediately responding to changes in the database, while stability means establishing a kind of continuity in the strategy of reasoning implemented by the inferencing mechanism. For the expert system to exhibit sensitivity and stability, IF-THEN rule based decision logic approach has been widely accepted [123, 183, 184, 187- 190].

Pordy et al. in 1968 and Macfarlane et al. in 1971 [64] stated that commercial computerized interpretation of ECG must be based on the rule based expert system approach. The first expert systems were developed as early as the late 1960s. However, it took until the 1970s before the research actually started on a large scale, in the field of medical expert systems. The earliest best known systems, that enabled the computer to solve different types of problems based on logic, was developed by A. Newell, H.A. Simon and J.C. Shaw known as GPS (General Problem Solver), first published in 1957 and then in 1963 [191, 192].

The best known expert system in medicine, MYCIN, was developed in the 1970s at Stanford University for treatment and diagnosis of a number of infectious diseases, in particular meningitis and bacterial septicaemia [193]. Other classic expert systems, developed in the 1970s, were INTERNIST-I (later named CADUCEUS), HEURISTIC DENDRAL, and XCON (previously called RI) [188]. Inspired by their success, expert systems have been built since then. Further works are reported in [194-204].

Windyga et al. in 1991 [205] developed an expert system (SETA) for the management of patients in the CCU environment. SETA suggested therapeutic actions for the treatment of serious arrhythmias that complicate the pathophysiological state of patients recovering from acute and suspected myocardial infarction. The system began by reasoning from the arrhythmia, diagnosed from the ECG signal, and progressed through its inference process by considering ECG changes (i.e. heart rate, QRS width), patient clinical data, patient history and therapeutic drug data, to reach the most appropriate actions for each particular patient.

The rule base expert systems, that mimic the decision-making process of the human expert, have been inducted in modern medical decision making, in real life situations, for the past few decades. Several modern computerized ECG interpretation systems are based on the decision logic approach that utilizes the well-established IF-THEN rule formalism, to generate diagnostic solutions. Such systems are highly data driven, i.e., large data sets composed of symbolic and numeric features, describing the signals under study in

their original form, are condensed into the process of IF-THEN decision rule making.

While many other methods, models algorithms and functions were developed to characterize recognize and classify arrhythmias, as observed through references reviewed above, computational analysis indicates that rule-based medical decision-making has gained a new momentum in recent years. The reasons are: simplicity, high accuracy, low computational complexity and acceptance of the method by human experts, physicians and patients.

The diagnostic rules of an expert system are fixed, once they are designed, and implemented as a software model. Also, it has been observed that these rules are data-specific and any minor adjustment leads to unwanted outcomes, unless the rules are generalized a priori or made robust enough to withstand minor data modifications. To account for these problems, faced by the rule-based medical decision-making systems, and also consider the advantages that these system offers, another area has emerged in computational intelligence, i.e., the *data mining* approach.

The growing volume of symbolic and numerical data in digital form, that enables error-free and high accuracy detections, has attracted researchers and practitioners to pay more attention to improve the conventional decision-making logic system. Autonomous and dynamic decision making, and generating robust decision rules that cater to the growing amount of data, are the assets of data mining algorithms.

Data mining is basically, discovering knowledge from the large sets of data, or, a process of learning, that generates general concepts or rules from specific examples, Kusiak et al. in 2001 [206], presented a data mining algorithm, the G-algorithm, to extract robust IF-THEN rules for identifying children with postoperative intra-atrial reentrant tachycardia.

A large set of features like age, primary cardiac diagnosis, secondary cardiac diagnosis, assessment of ventricular function by echocardiogram, clinically documented arrhythmia following the surgery, sino-atrial conduction time, atrioventricular Wenckebach cycle length etc. were used to frame the decision rules by employing the G-algorithm, that presented a rewarding performance as compared to the statistical techniques attempted earlier with the same feature set.

Kundu et al. in 2000 [185] critically reviewed different ECG interpretation systems providing a comparative assessment of performances of all these approaches viz., ECG modeling using AND/OR graph, a rule based approach, a procedural semantic network based approach, and fuzzy-logic-based approach.

Mitra et al. in 2006 [184] presented an ECG classification system based on rough-set analysis that is usually a collection of IF-THEN rules which give rise to a rule-based expert system that provides offline ECG classification for cardiac disease identification. The main advantage of this technique is that the classifier incorporates more human-like decision making.

Tsipouras et al. [207] in 2006 compared three different methodologies for creation of fuzzy expert systems viz., a neuro-fuzzy approach, a knowledge-based approach and a novel methodology, based on rule-extraction. The adaptive neuro-fuzzy information system (ANFIS) was used to automatically generate a fuzzy expert system.

In the knowledge-based approach and the rule-extraction methodology, the model was described by crisp rules, provided by medical experts in the first case or extracted using data mining techniques in the second. The rules were transformed into a set of fuzzy rules, creating a fuzzy model. In either case, the adjustment of the model's parameters was performed via a stochastic global optimization procedure. All three approaches were applied to a medical domain problem, the cardiac arrhythmic beat classification. The ability to interpret the decisions made from the created fuzzy expert systems was a major advantage compared to other "black box" approaches. The details of the methodology were also reported by Exarchos et al. in 2007 [153].

CONCLUSION

Reliable detection of arrhythmias based on digital processing of ECG signals is vital in providing suitable and timely treatment to a cardiac patient. Computerized arrhythmia interpretation systems are very much needed as they aid a cardiologist in taking crucial decisions while diagnosing abnormal heart rhythms. However, due to corruption of ECG signals with multiple frequency noise and presence of multiple arrhythmic events in a cardiac rhythm, computerized interpretation of abnormal ECG rhythms is a challenging task.

Computerized ECG interpretation to detect arrhythmias (off-line or on-line) is a process of ECG data acquisition, waveform recognition, measurement of wave parameters and rhythm classification. Substantial progress has been made over the years in improvising techniques for signal conditioning, extraction of relevant wave parameters and rhythm

classification. However, many problems and issues, especially those related to detection of long P and T peaks and reliable analysis of multiple arrhythmic events etc., still need to be addressed in a more comprehensive manner to brighten the prospect of commercial automated arrhythmia analysis in mass health care centers.

From the literature survey it is observed that besides conventional computing techniques such as FFT, DFT and wavelet transforms etc., frequent usage of sophisticated artificial intelligent tools such as expert systems has also been reported. Knowledge-based expert systems that are IF-THEN rule based systems form a major part of clinical decision support systems in practice, since the decision making process in such systems is easily followed by a cardiologist. Nonknowledge-based expert systems that are not rule based employ hybrid AI techniques such as fuzzy-neural networks or expert systems using genetic algorithms.

Although, hybrid AI systems are fast and efficient, further research is needed to make them more reliable in clinical diagnostics. Also, these systems provide little insight into how decisions are made or what is the declarative knowledge structure, thereby creating difficulties for cardiologists to understand such 'black-box' systems, and hence eliciting their disapproval for implementation of such systems in clinical situations. Such systems are best suited to problems where the expert system intends to make reasoned judgments for huge databases, and to give assistance in a complex area in which human skills are fallible or scarce.

Also, uncertainty in ECG classification systems need to be addressed in cases where the signal content is insufficient or the data recording is corrupted by excessive noise; hybrid AI tools may tackle the issues related to uncertainty to a great extent providing efficient solutions.

To conclude, some possible future research directions in development of expert systems for arrhythmia analysis and interpretation using ECG signals may include:

(i) Informative and rigorous knowledge representation scheme that can document real-time/ clinical ECG data with better precision and accuracy;

(ii) Reliable diagnostic inferencing mechanism that can provide efficient reasoning for ECG records having different types and degrees of uncertainties,

(iii) Provisions to automatically upgrade existing reasoning rules on the basis of advanced AI techniques when the interpretation of ECG data inferred by the expert system is appended by a cardiologist/ physician.

(iv) Interactive schemes that can provide useful two-way communication between an ailing patient suffering from heart disorders and a cardiac physician/ surgeon via advanced methods of telemedicine.

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